Freddie Mac CRT Quarterly Webcast

July 2022

FreddieMac
Single-Family | Credit Risk Transfer

Today's Speakers

Mike Reynolds

Vice President

Single-Family Credit Risk Transfer

Michael Bradley

Senior Vice President

Modeling, Econometrics, Data Science and Analytics

Latest Resources

Now available on crt.FreddieMac.com

CRTcast E5:
SYNDICATION'S ROLE IN NEW ISSUE CRT

Freddie Mac Single-Family | Credit Risk Transfer

CRTcast | PODCAST

Christie Tintle
Managing Director and Head of Wells Fargo Securities' Asset-Backed Finance Syndicate Team

Mike Reynolds
Vice President
Single-Family Credit Risk Transfer

Clarity Recognition

BANKING TECH AWARDS | Brought to you by FINTECH FUTURES

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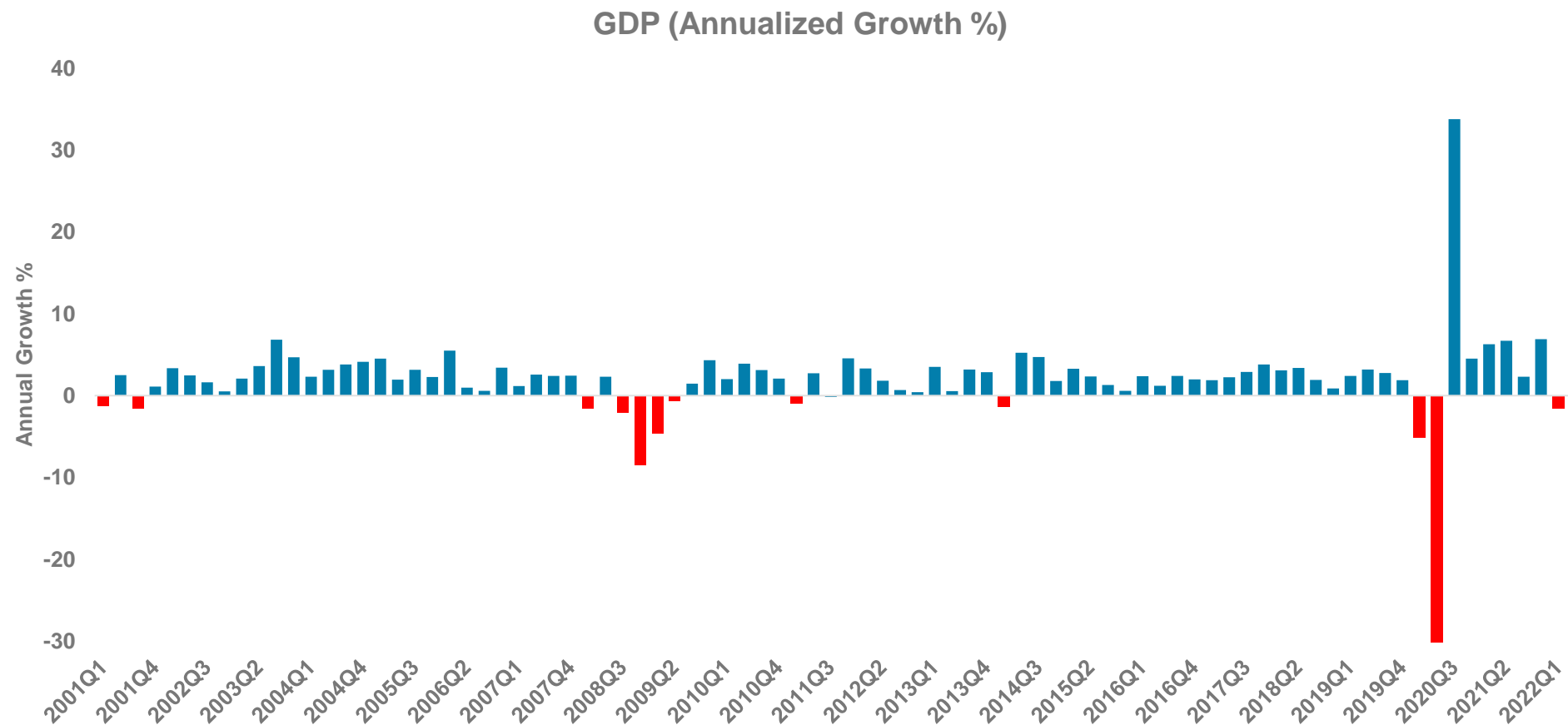
Bronze Stevie® Winner: Data Tools & Platforms

Also Available in the Resource Hub
- Investor Day Recording

Economic and Housing Update

GDP Declined by 1.6% in Q1 and 0.9% in Q2 2022

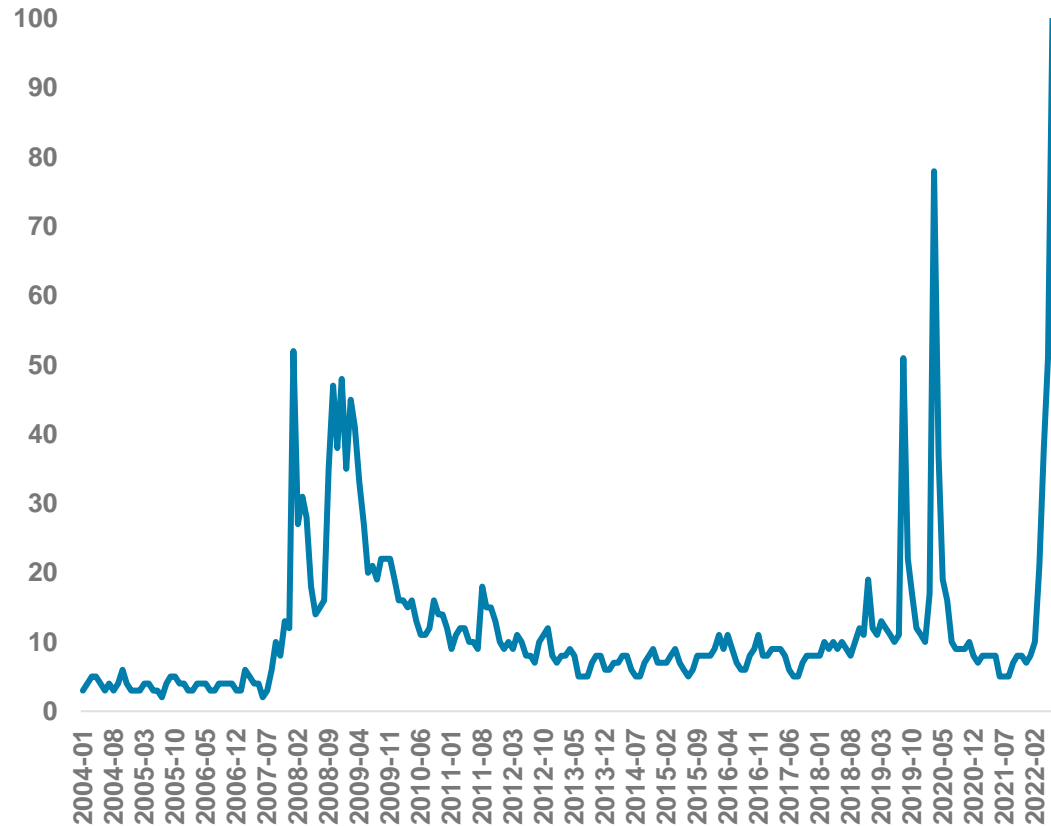
GDP (Annualized Growth %)

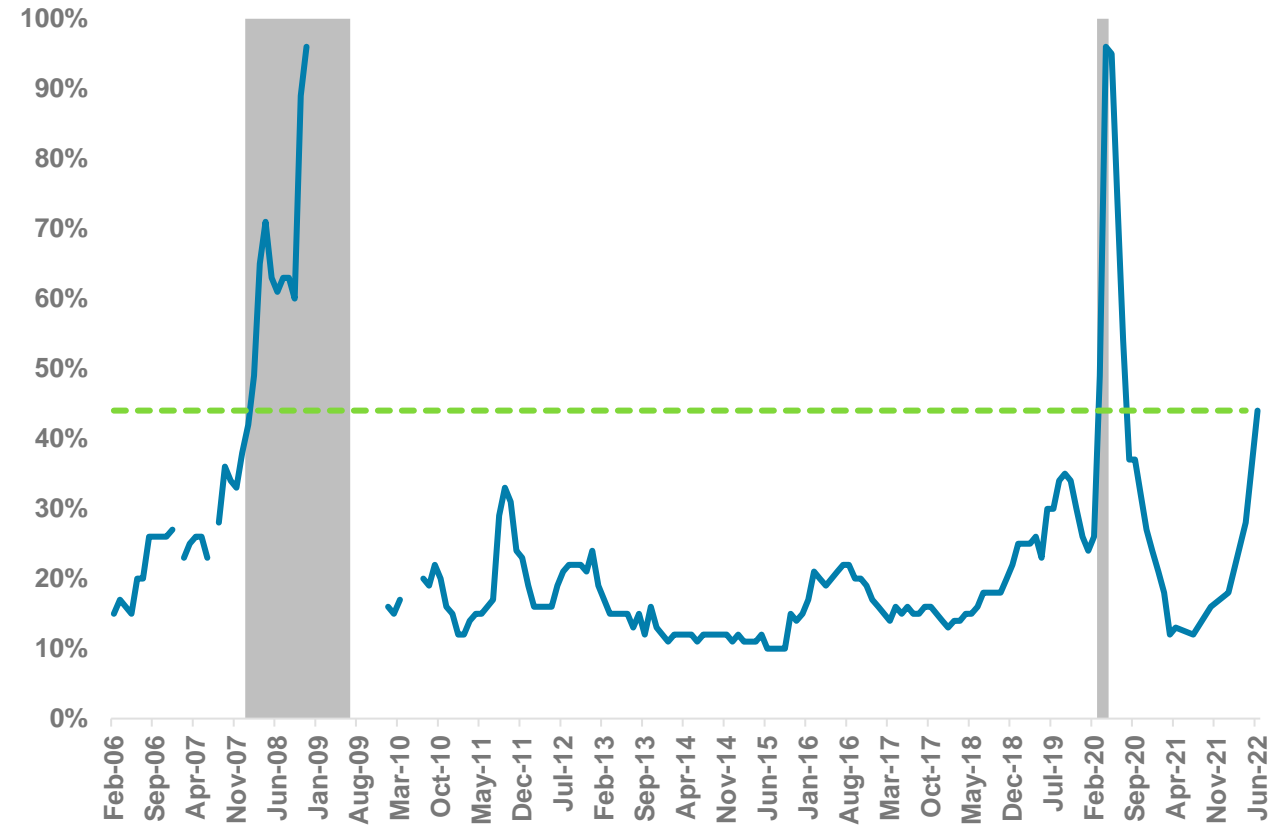*Source: U.S. Bureau of Economics Analysis (BEA)*

Recession Risk Rising

Google Trends - Recession
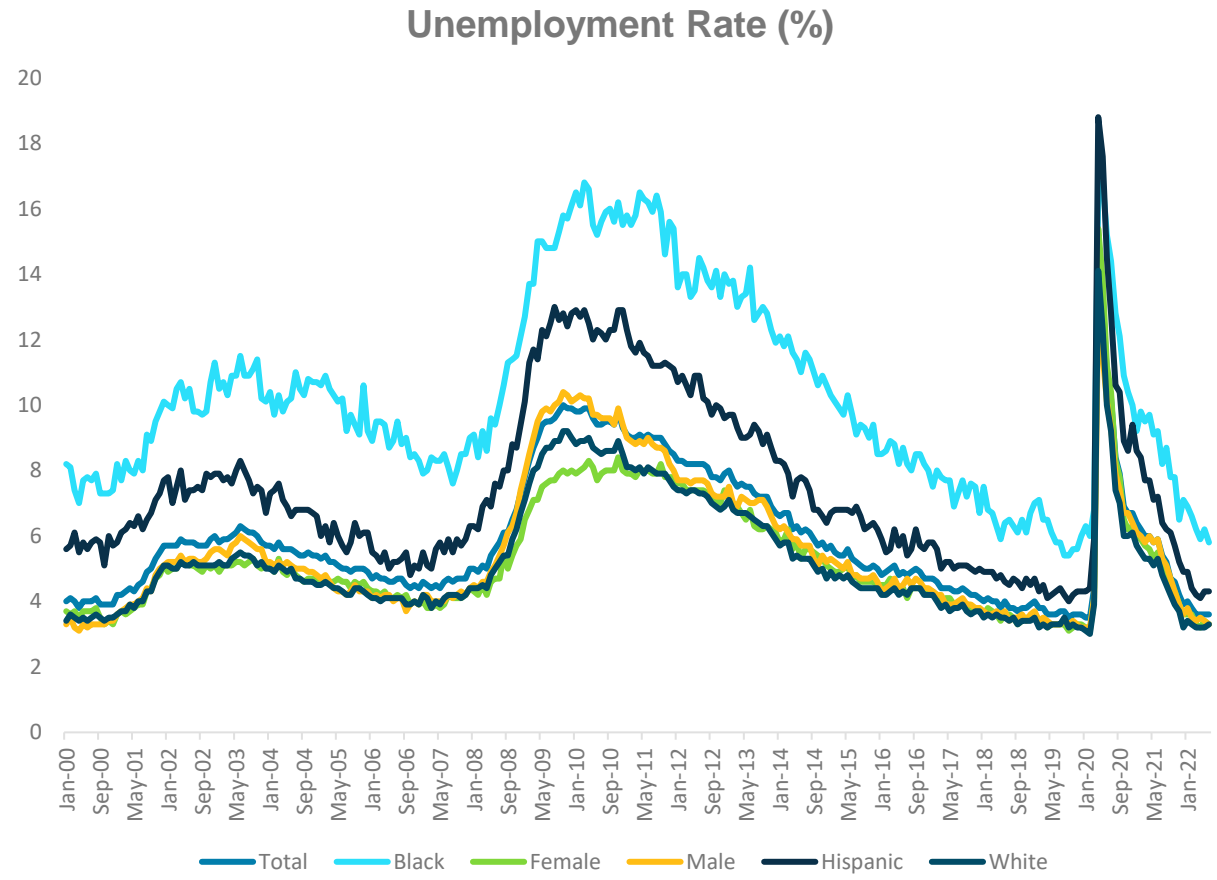
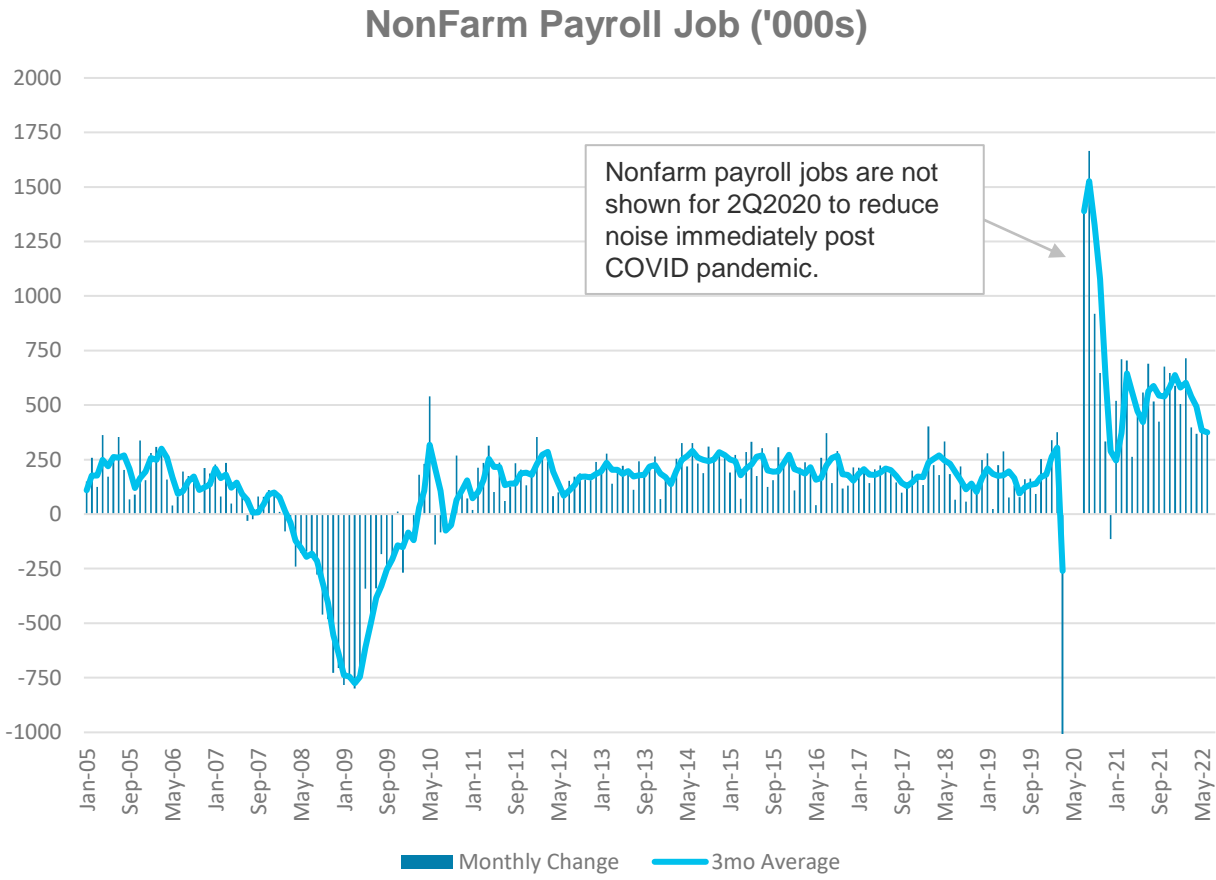Wall Street Journal Recession Probability

Source: GOOGLE Trends, Wall Street Journal
Note: Numbers represent search interest relative to the highest point on the chart for the given region and time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. A score of 0 means there was not enough data for this term.

Labor Market Recovery Strong

Unemployment Rate at 3.6%

NonFarm Payroll Job ('000s)

Nonfarm payroll jobs are not shown for 2Q2020 to reduce noise immediately post COVID pandemic.

Legend: Monthly Change — 3mo Average

Unemployment Rate (%)

Legend: Total — Black — Female — Male — Hispanic — White

Source: Bureau of Labor Statistics

Strong Consumption Led to Historic Labor Market Recovery

Monthly YoY Job Growth

Job Openings per Unemployed Person

Quits Rate
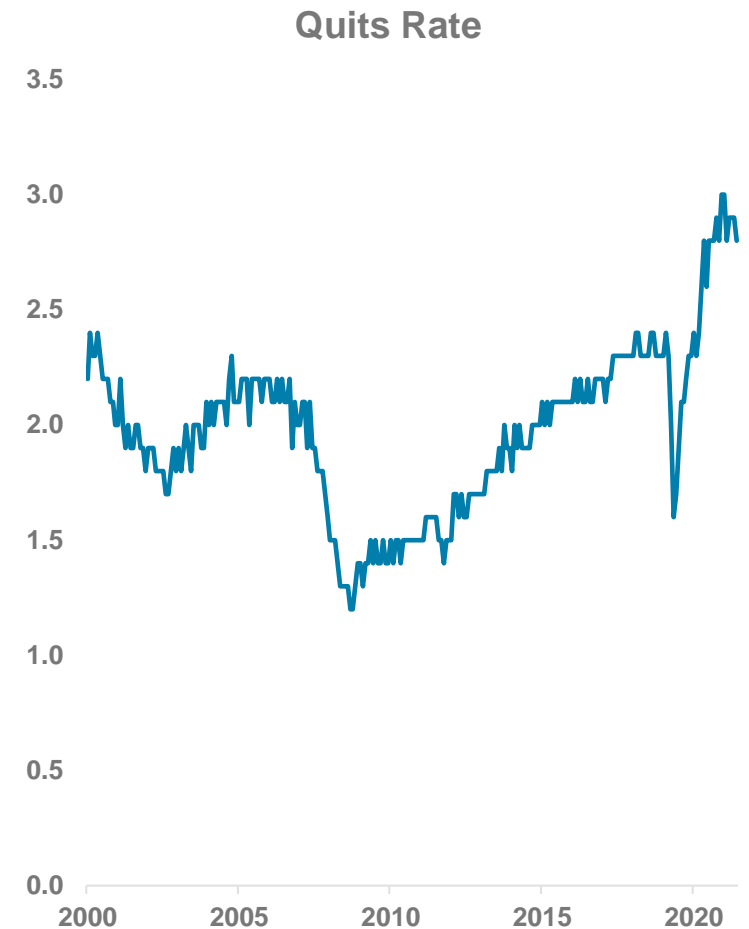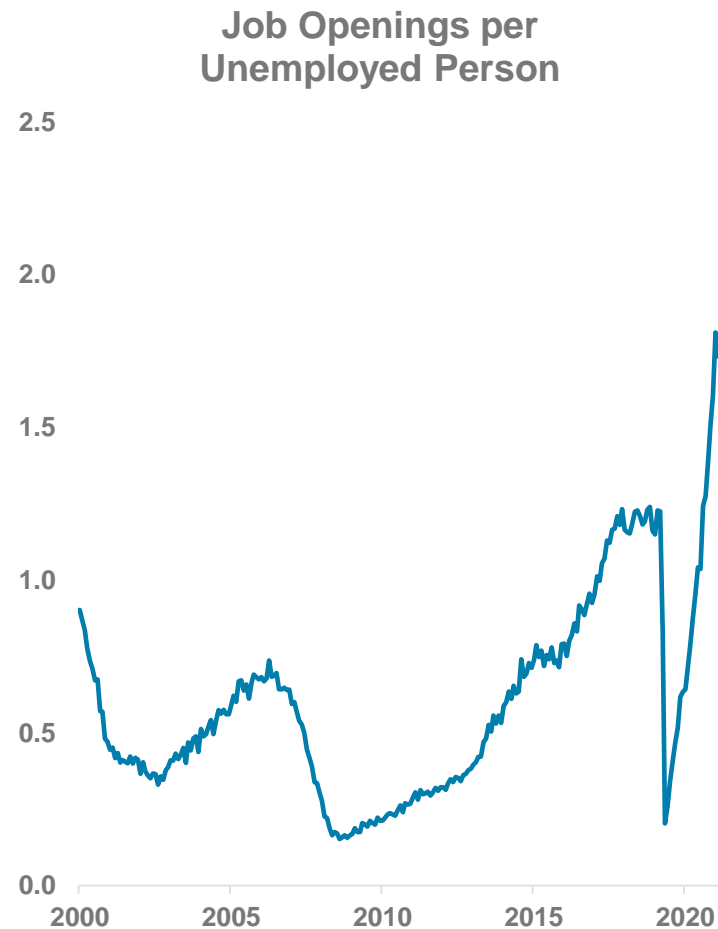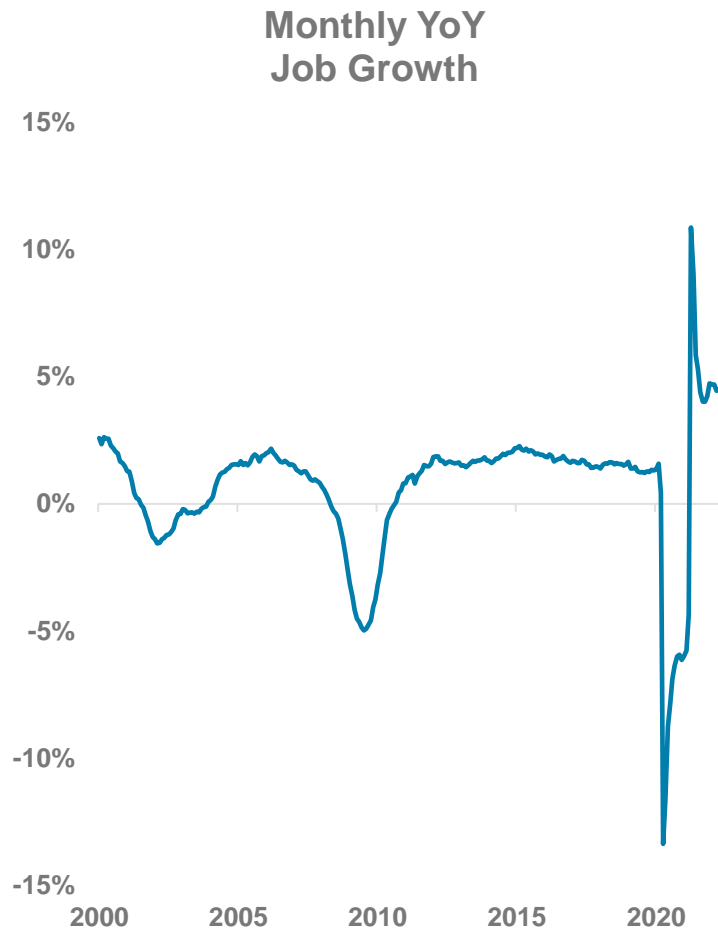
Source: Bureau of Labor Statistics

Inflation Remains at 40-year High

Inflation Measures

CPI — Core CPI

Goods vs Services Inflation

Goods — Services

Goods, 7.1%

Services, 5.5%
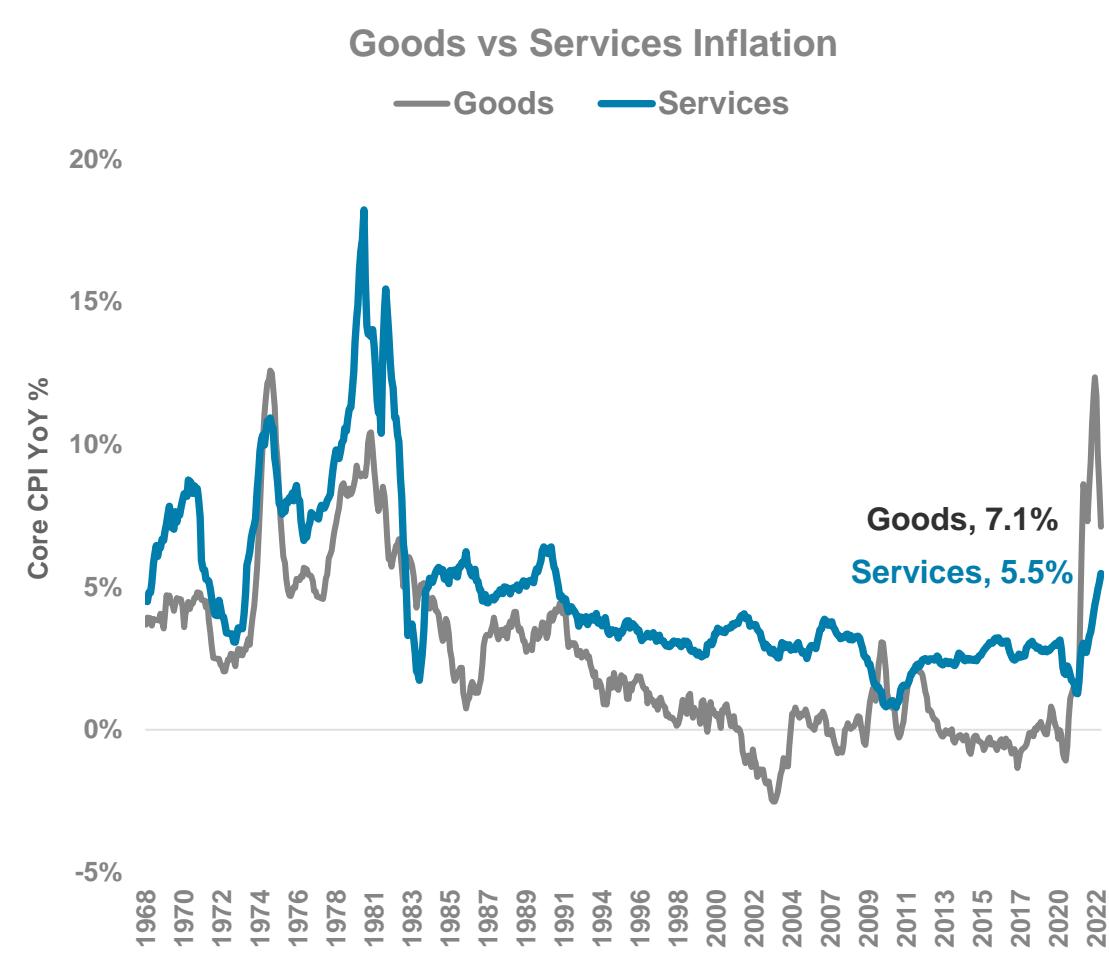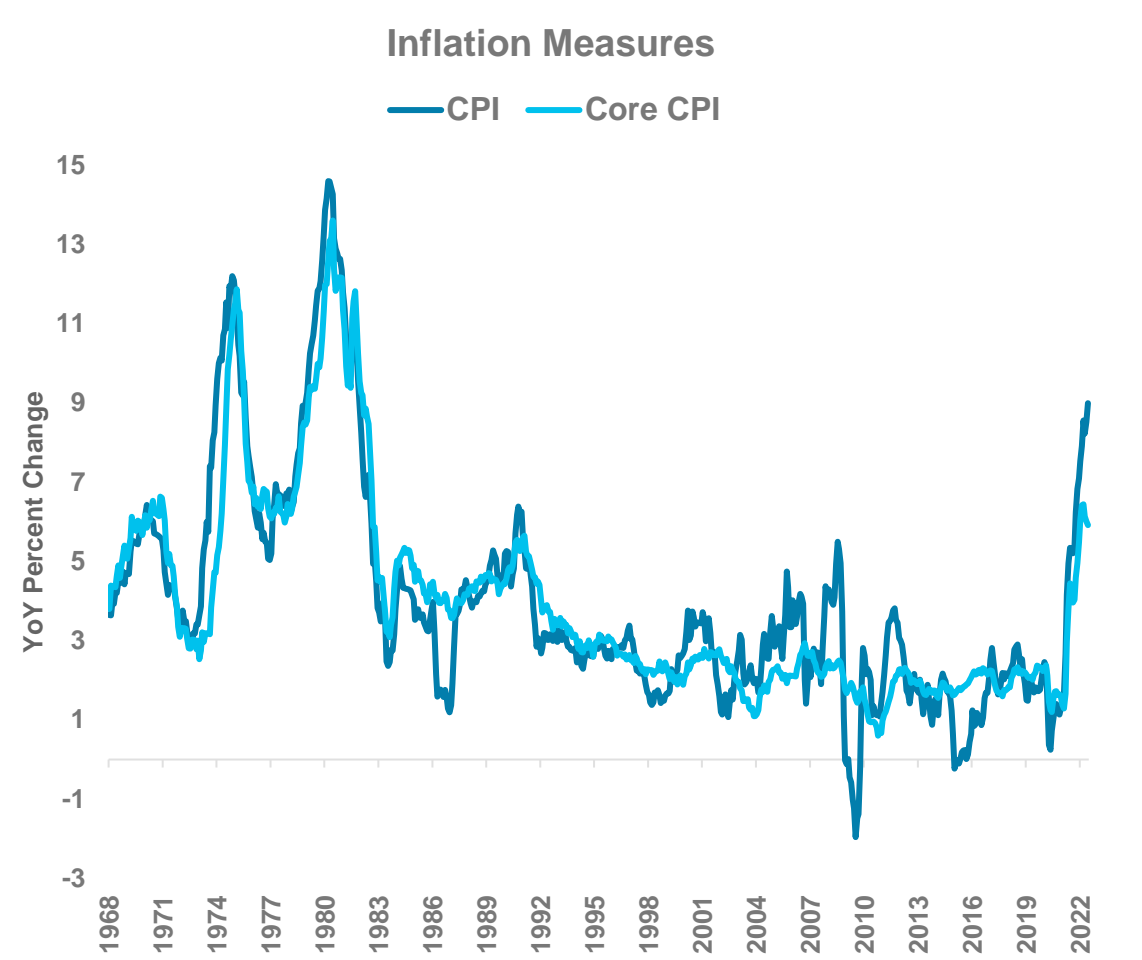
Source: Bureau of Labor Statistics; Consumer Price Index for All Urban Consumers

Mortgage Rates up 2.7%; Biggest 1-year Increase This Century

Recent Mortgage Interest Rates Very Volatile
U.S. weekly average 30-year fixed mortgage rate (%)

5.54

Source: Freddie Mac Primary Mortgage Market Survey

Mortgage Rates Up Almost 3 Percentage Points
12-month change in U.S. 30-year fixed mortgage rates (%)

2.74

Source: Freddie Mac Primary Mortgage Market Survey
change computed using last observed weekly value in each month

High Mortgage Rates and Home Values Reduce Affordability

dotted line shows equal payment combinations of rate and loan size
each dot value for week 28 of the year (latest week available in 2022)

2022 loan size at 2019 rate

Average conventional purchase loan size ($)

Average 30-year fixed mortgage rate (%)
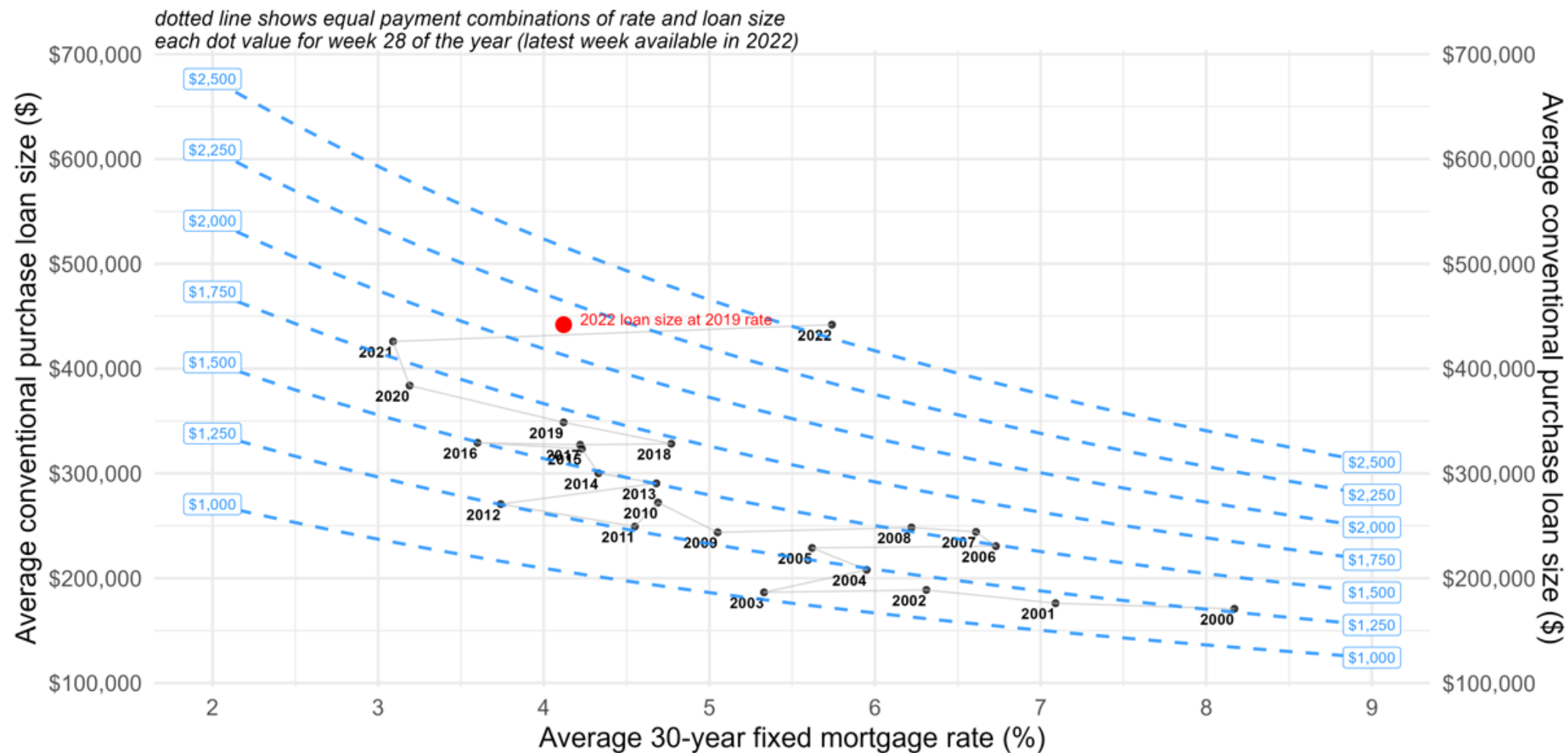
Data source: MBA
payments principal and interest (P&I) for 30-year fixed mortgage

Mortgage Originations Set to Decline as Refinances Fade

Annual single-family mortgage originations ($Trillions)

Refinance ($T)
Purchase ($T)

Year	Refinance	Purchase	Total
2012	1.5	0.6	2.1T
2013	1.1	0.8	1.9T
2014	0.5	0.8	1.3T
2015	0.8	0.9	1.7T
2016	1.0	1.0	2.1T
2017	0.7	1.1	1.8T
2018	0.5	1.2	1.7T
2019	1.1	1.3	2.4T
2020	2.9	1.6	4.4T
2021	2.8	2.0	4.8T
2022F	0.9	2.0	2.8T
2023F	0.5	1.9	2.3T
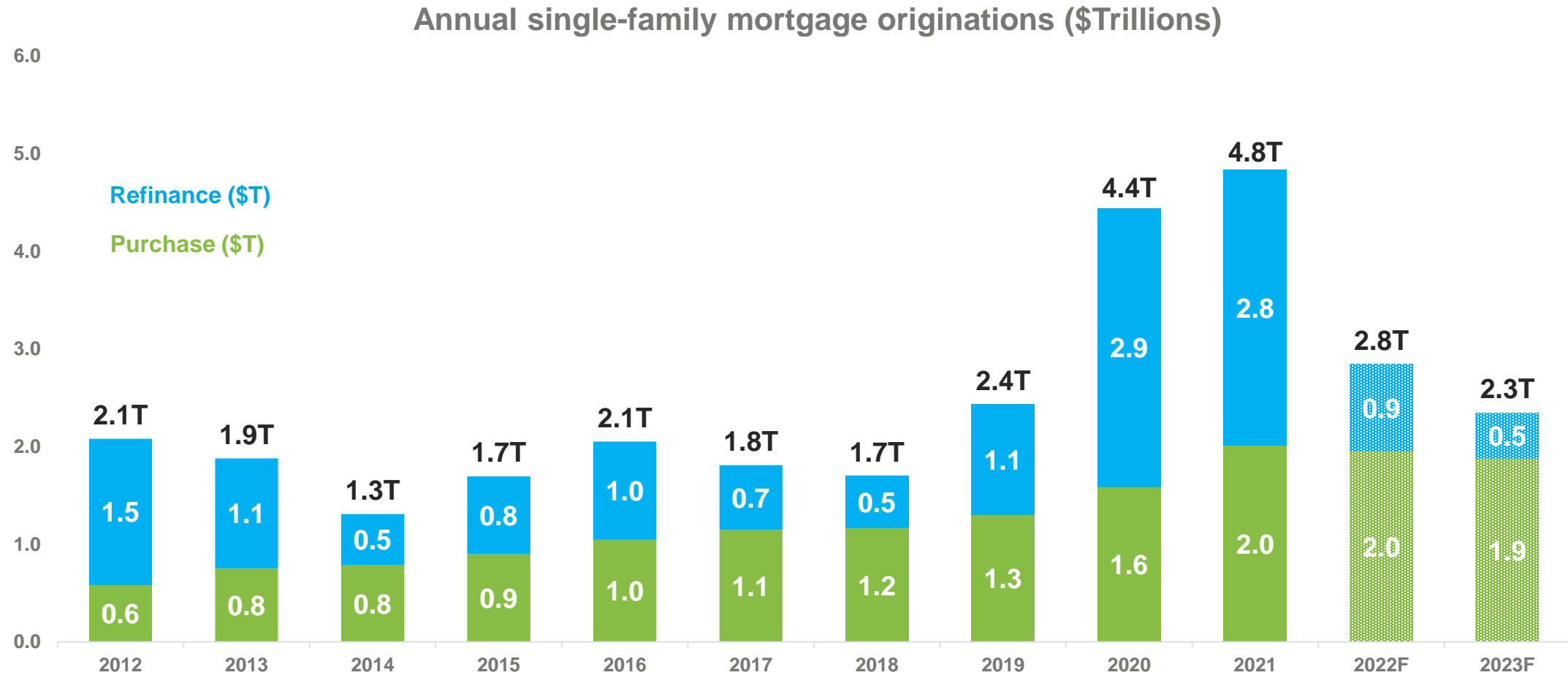
Source: Freddie Mac Q2 2022 Economic and Housing Research Outlook
Note: Totals may not add due to rounding. Including only first liens.

Inventory Remains Low Despite Recent Increases

Total Home for Sale (Ths. #, SA)
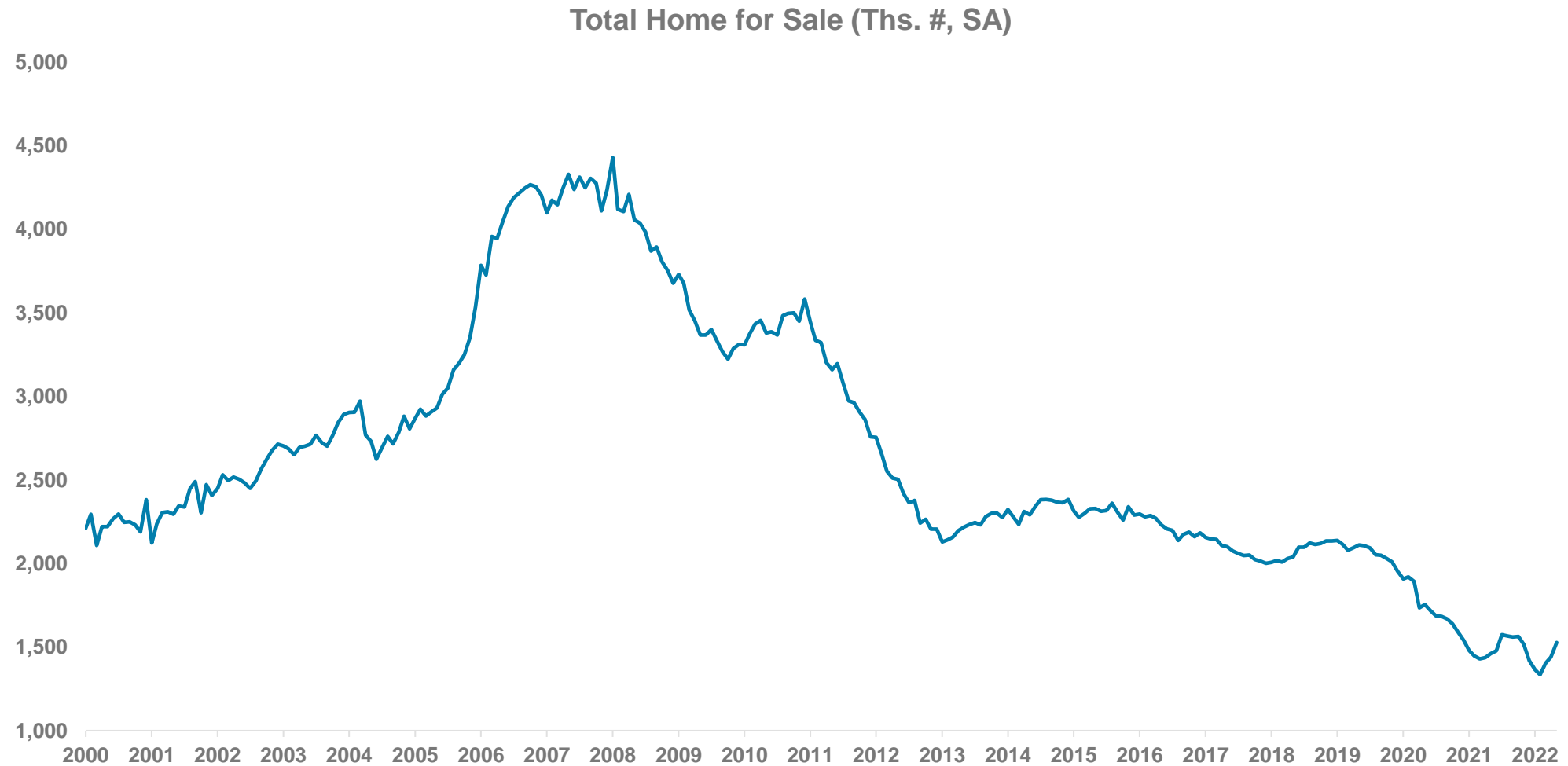
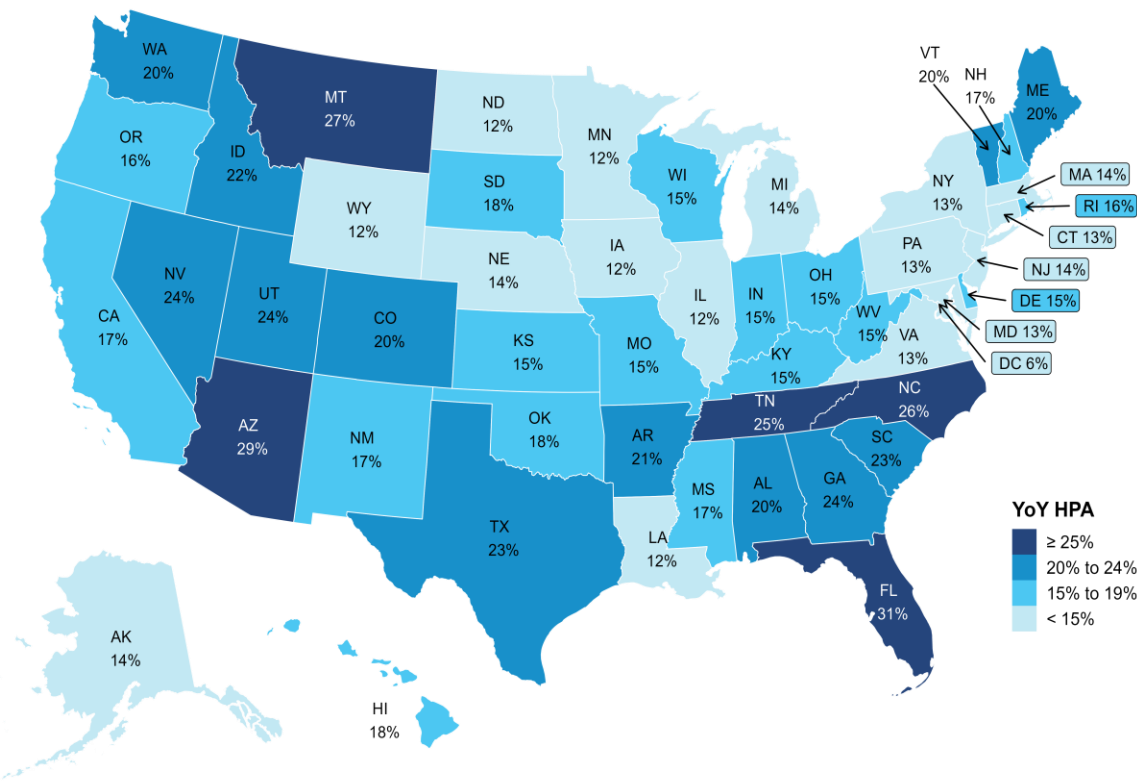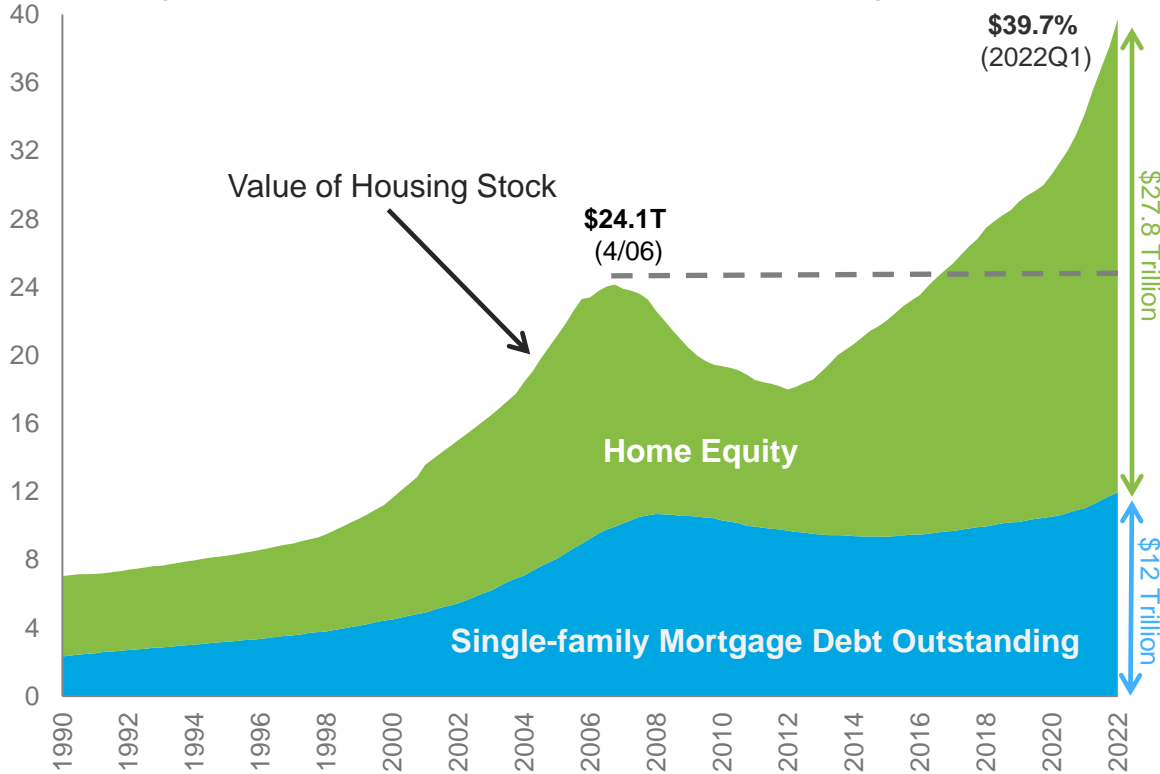*Source: U.S. Census Bureau, NAR.*

Robust Demand, Limited Supply Put Intense Pressure on House Prices

U.S. House Prices Increased 18% YOY in May 2002

YoY HPA
- ≥ 25%
- 20% to 24%
- 15% to 19%
- < 15%

WA 20%, OR 16%, ID 22%, MT 27%, ND 12%, MN 12%, VT 20%, NH 17%, ME 20%, WI 15%, MI 14%, NY 13%, MA 14%, RI 16%, CT 13%, NJ 14%, DE 15%, MD 13%, DC 6%, SD 18%, WY 12%, IA 12%, NE 14%, IL 12%, IN 15%, OH 15%, PA 13%, WV 15%, VA 13%, NV 24%, UT 24%, CO 20%, KS 15%, MO 15%, KY 15%, CA 17%, AZ 29%, NM 17%, OK 18%, AR 21%, TN 25%, NC 26%, SC 23%, MS 17%, AL 20%, GA 24%, TX 23%, LA 12%, FL 31%, AK 14%, HI 18%

Rising Home Prices Help Build Equity for Existing Homeowners

$39.7% (2022Q1)

$24.1T (4/06)

Value of Housing Stock

Home Equity

Single-family Mortgage Debt Outstanding

$27.8 Trillion

$12 Trillion

Source: Freddie Mac House Price Index, May 2022.
The Freddie Mac House Price Index for the U.S. is a value-weighted average of the state indexes where the value weights are based on Freddie Mac's single-family credit guarantee portfolio. Other indices of home prices may have different results, as they are determined using different pools of mortgage loans and calculated under different conventions. The Freddie Mac House Price Index for the U.S. is a non-seasonally adjusted monthly series. Percent changes were rounded to nearest whole percentage point.

Note: Value of U.S. housing stock includes homes with and without underlying mortgages. U.S. home equity is the difference between the value of the U.S. housing stock and the amount of U.S. single-family mortgage debt outstanding.

Source: Federal Reserve Board's Financial Accounts of the United States, Table B. 101. Data as of Jun 9, 2022

# New Mortgage Borrowers Have Exceptional Credit

Quarterly Report on Household Debt and Credit: Credit Score at Origination – Mortgages – Median
(Score, NSA)

Federal Reserve Bank of New York (FRBNY): Quarterly Report on Household Debt and Credit [HHDC] - Credit Score at Origination - Mortgages

# Historically Low Rate of Newly Delinquent Mortgage Borrowers

Quarterly Report on Household Debt and Credit: New Delinquent Balances by Loan Type – Mortgages

(%, NSA)
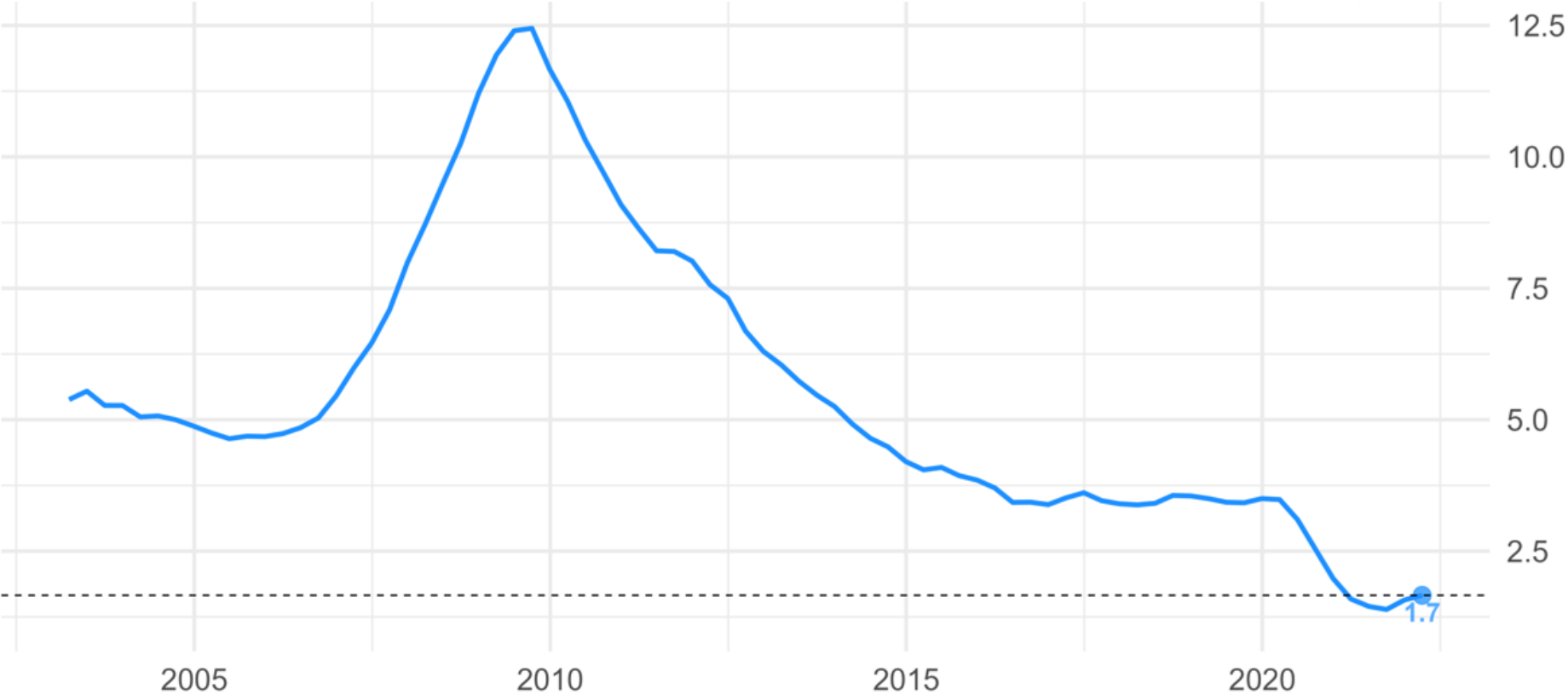
Federal Reserve Bank of New York (FRBNY): Quarterly Report on Household Debt and Credit [HHDC] - New Delinquent Balances by Loan Type

Forbearance and Other Policies Have Nearly Eliminated Foreclosures
Quarterly Report on Household Debt and Credit: Consumers with New Foreclosures and Bankruptcies
(Ths. #, NSA)
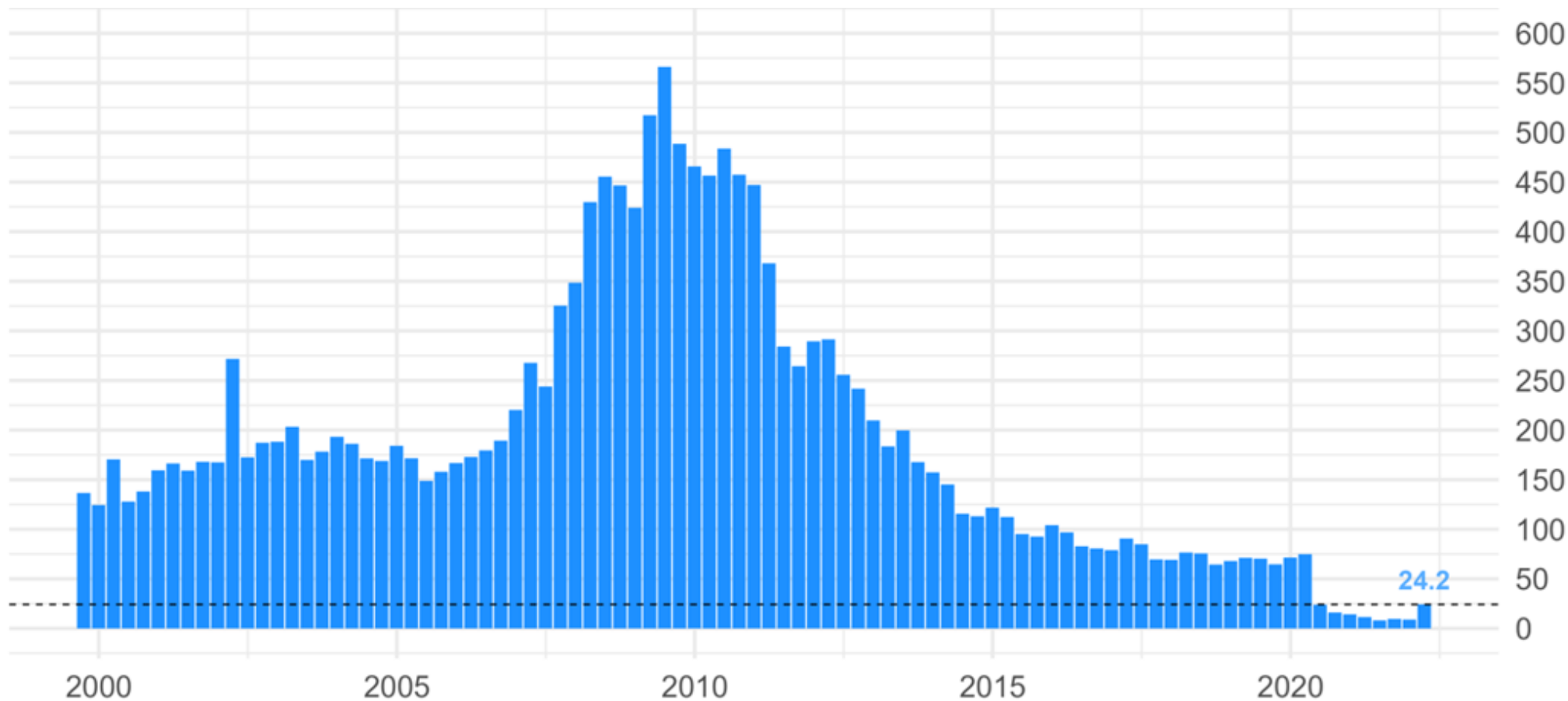
Federal Reserve Bank of New York (FRBNY): Quarterly Report on Household Debt and Credit [HHDC] - Number of Consumers with New Foreclosures and Bankruptcies
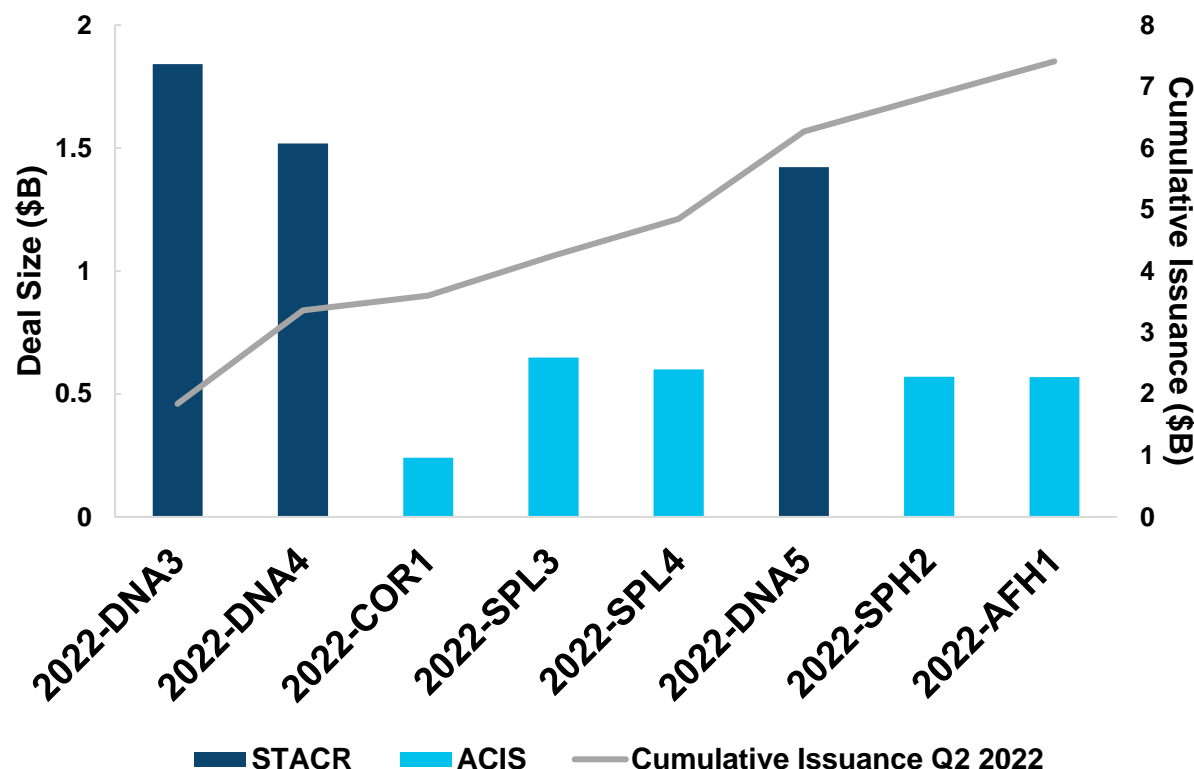
CRT Update

Programmatic Issuance and Broad Participation
Commitment to the CRT Market

Q2 2022 Issuance

Record Issuance in first half of 2022
$15 B issued including 6 STACR and 8 ACIS

$7.4 Billion Q2 Issuance Volume
Another Large Issuance Quarter for CRT

New Deal Types Introduced
2022-COR1 and 2022-AFH1

29 New Participants in first half of 2022
162 unique Investors/(Re)insurers across STACR/ACIS

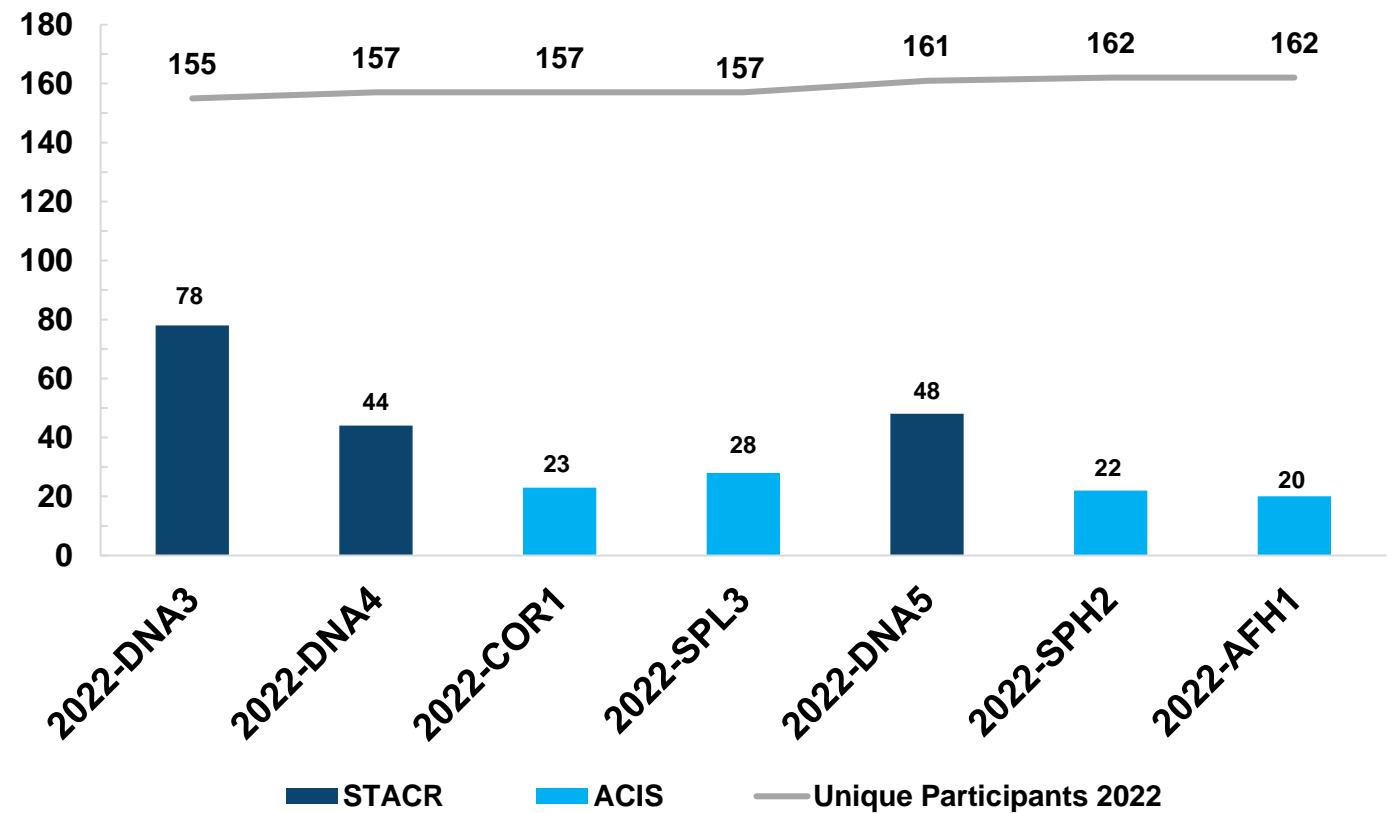**Second Tender Offer of 2022 Executed**
$2B+ tendered in STACR 2022-TO2

Source: Freddie Mac, as of June 2022. **Note:** Amounts may not add up due to rounding.
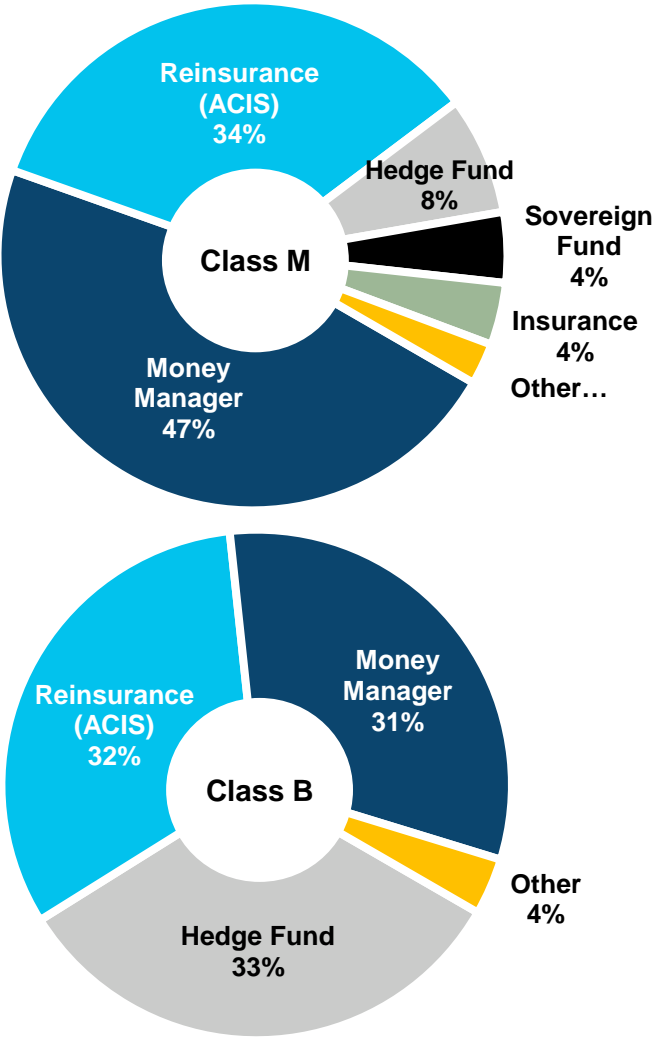
Investor Participation

Commitment to the CRT Market

Q2 2022 Deal Participation

Chart data:
- Unique Participants 2022: 155, 157, 157, 157, 161, 162, 162
- 2022-DNA3 (STACR): 78
- 2022-DNA4 (STACR): 44
- 2022-COR1 (ACIS): 23
- 2022-SPL3 (ACIS): 28
- 2022-DNA5 (STACR): 48
- 2022-SPH2 (ACIS): 22
- 2022-AFH1 (ACIS): 20

Legend: STACR, ACIS, Unique Participants 2022

Participant Profile Since 2019

Class M
- Reinsurance (ACIS) 34%
- Hedge Fund 8%
- Sovereign Fund 4%
- Insurance 4%
- Other…
- Money Manager 47%

Class B
- Reinsurance (ACIS) 32%
- Money Manager 31%
- Other 4%
- Hedge Fund 33%

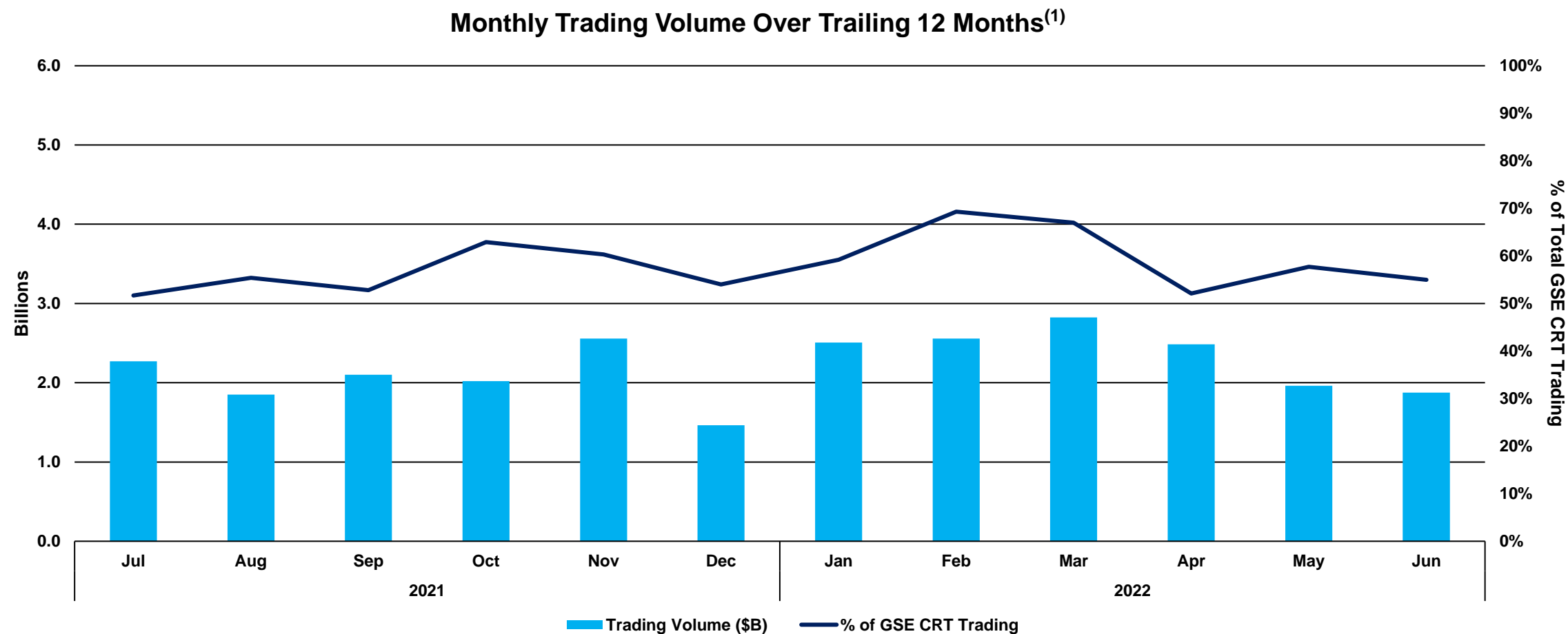**Source**: Freddie Mac, all data as of June 2022. **Note:** Amounts may not add up due to rounding.

STACR Secondary Trading Volumes

Market leader in GSE CRT Secondary Trading

Monthly Trading Volume Over Trailing 12 Months[1]

Legend: Trading Volume ($B), % of GSE CRT Trading

X-axis: Jul, Aug, Sep, Oct, Nov, Dec (2021), Jan, Feb, Mar, Apr, May, Jun (2022)

Left Y-axis: Billions (0.0 – 6.0)

Right Y-axis: % of Total GSE CRT Trading (0% – 100%)

CRT Performance: On-the-Run Actual Loss Transactions

Strong portfolio performance across vintages

119
Transactions Issued

0.3
Average bps of Loss Per Transaction

4
Retired Transactions

36
Transactions with No Losses

99
Transactions with <1bp of Loss

0
Transactions with >2 bps of Loss

Weighted Average Cumulative Net Losses by Issuance Year (bps)

Bar chart — WA Cumulative Net Loss (bps) by issuance year:
- 2015: ~1.4
- 2016: ~0.98
- 2017: ~0.56
- 2018: ~0.5
- 2019: ~0.2
- 2020: ~0.02
- 2021: 0
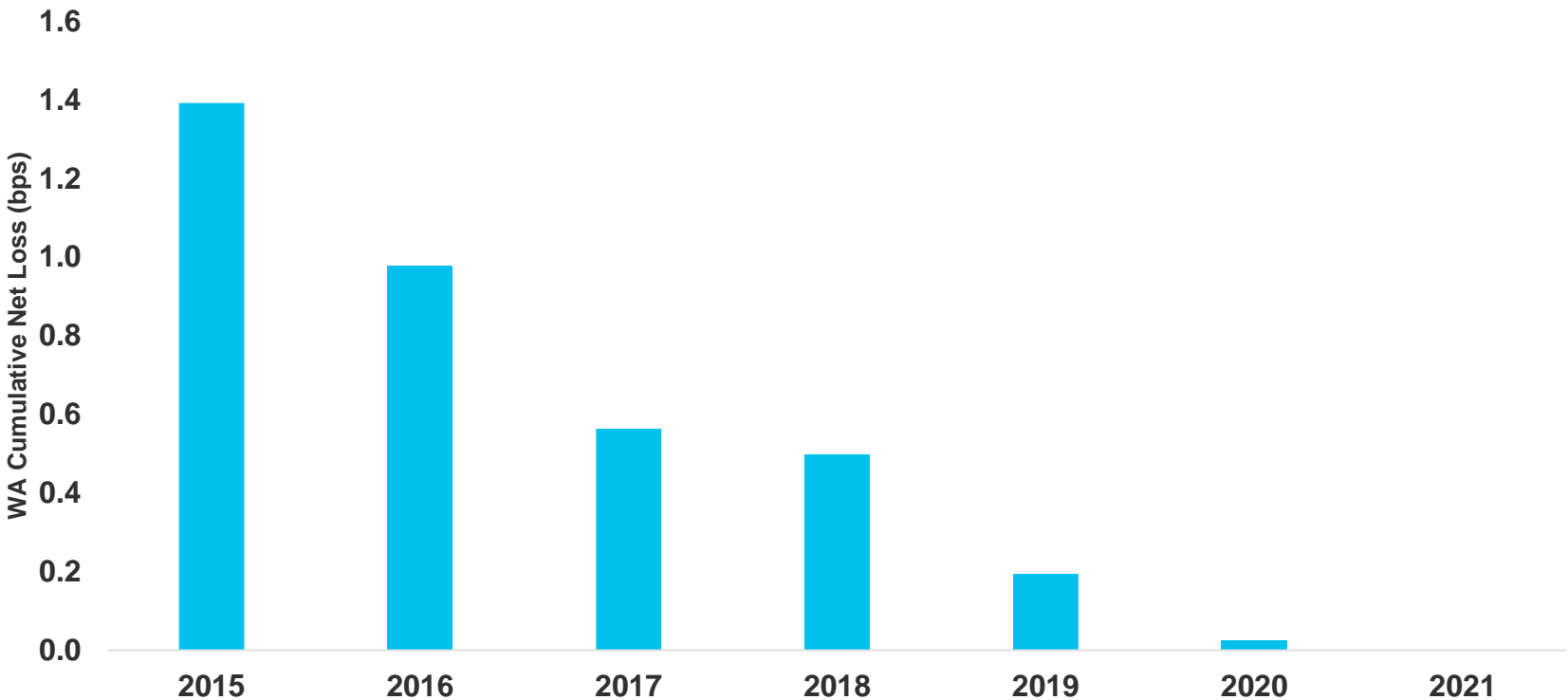
Source: Freddie Mac monthly remittance data for STACR and ACIS 30 year low and high LTV transactions, as of June 2022. Retired transactions excluded from transaction loss counts.

COVID-19 Performance Recovery

Delinquency and forbearance trends continue to improve for Freddie Mac
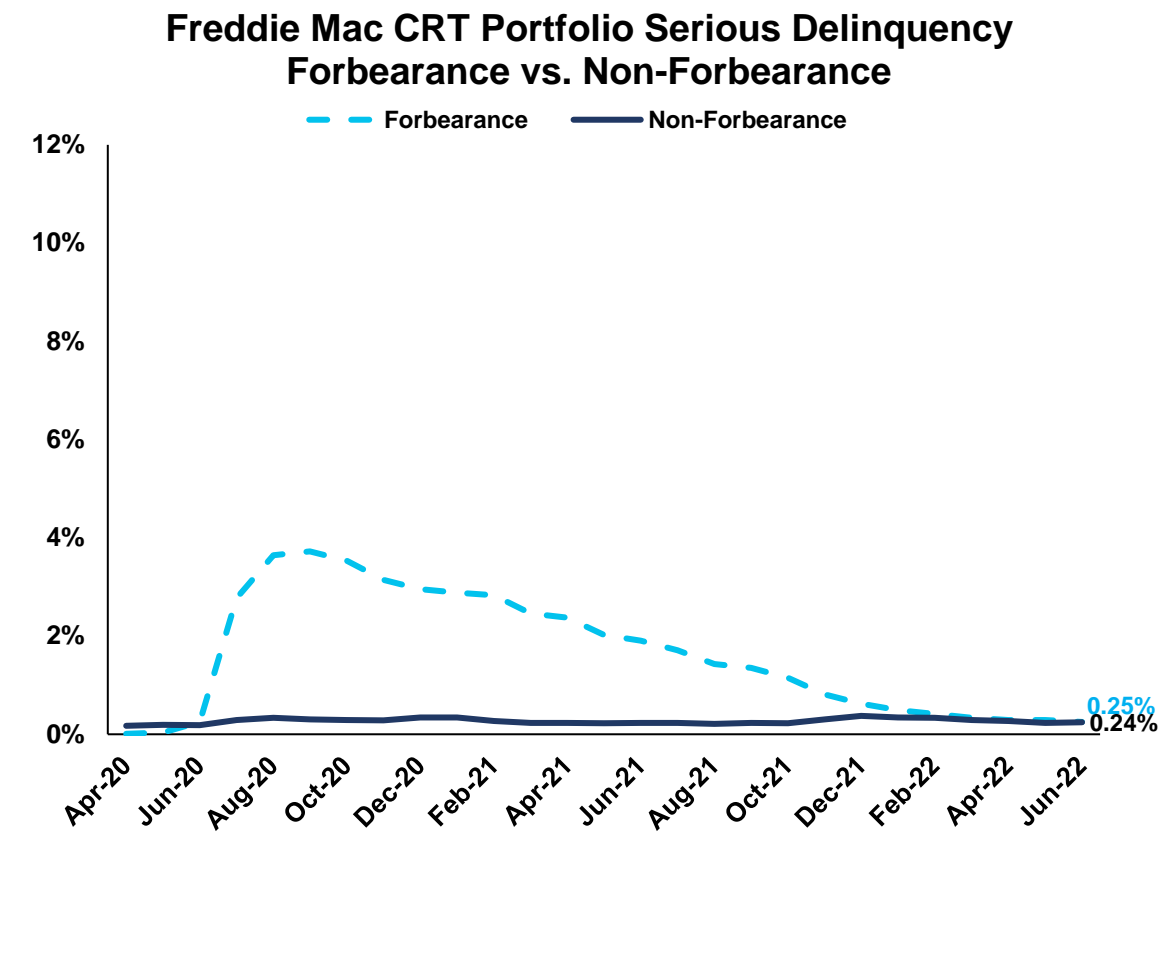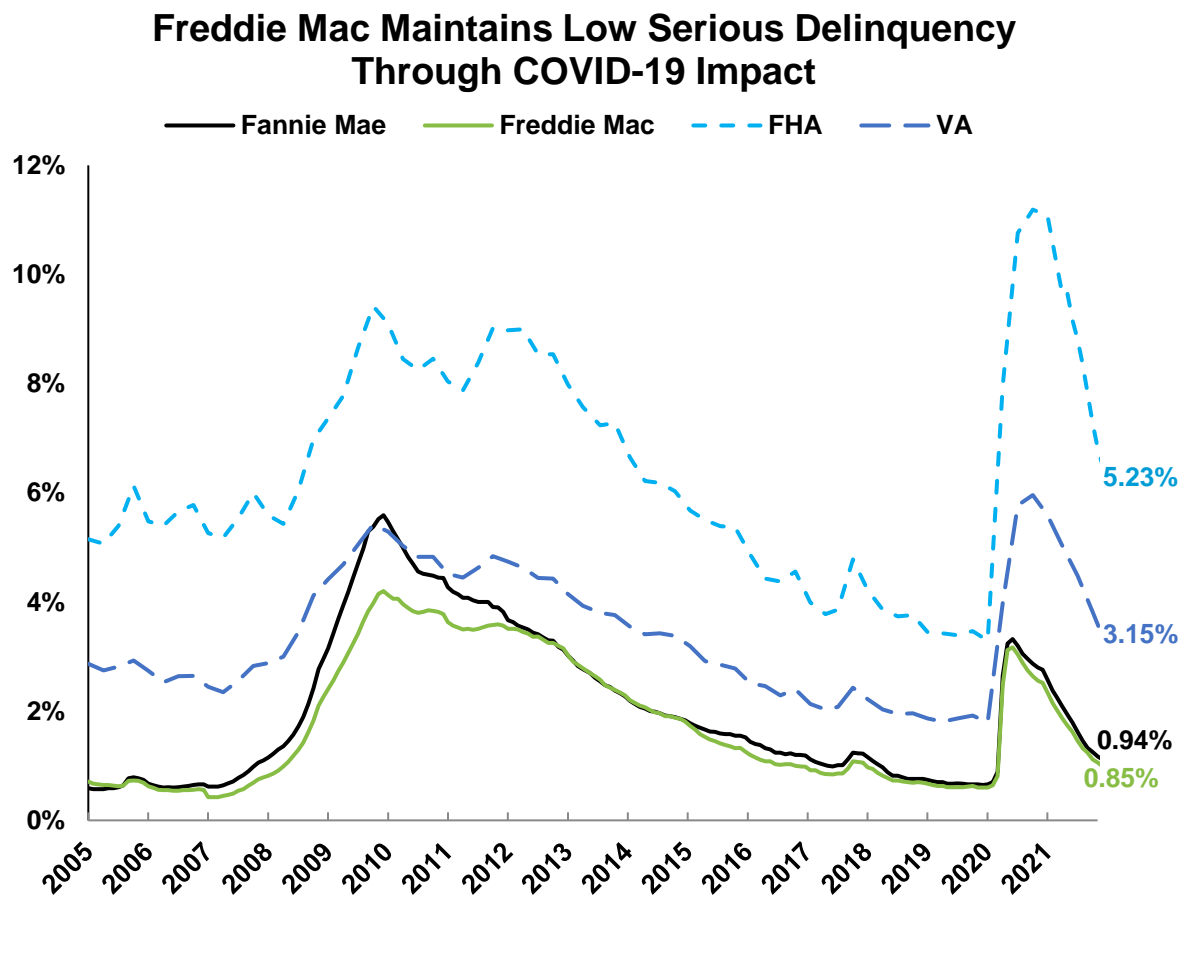
Freddie Mac Maintains Low Serious Delinquency Through COVID-19 Impact

Legend: —— Fannie Mae —— Freddie Mac - - - FHA — — VA

5.23%
3.15%
0.94%
0.85%

Freddie Mac CRT Portfolio Serious Delinquency Forbearance vs. Non-Forbearance

Legend: - - - Forbearance —— Non-Forbearance

0.25%
0.24%

Forbearance Resolution

Modification Volumes Have Risen in Recent Months

Forbearance by Period

Legend: New FB Loans | FB Exits | Total Active FB

Modification and Payment Deferral Volume

Legend: Mod | PD
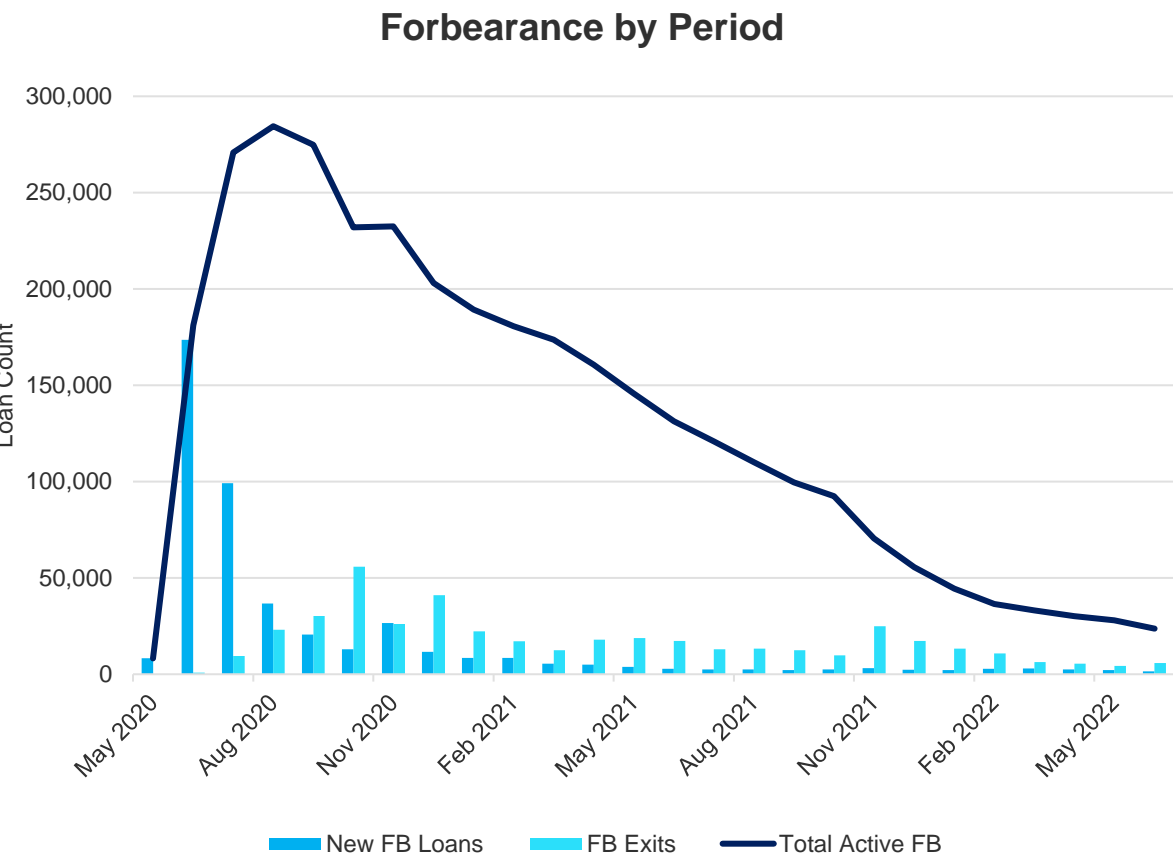
Source: Freddie Mac CRT Disclosure Data.
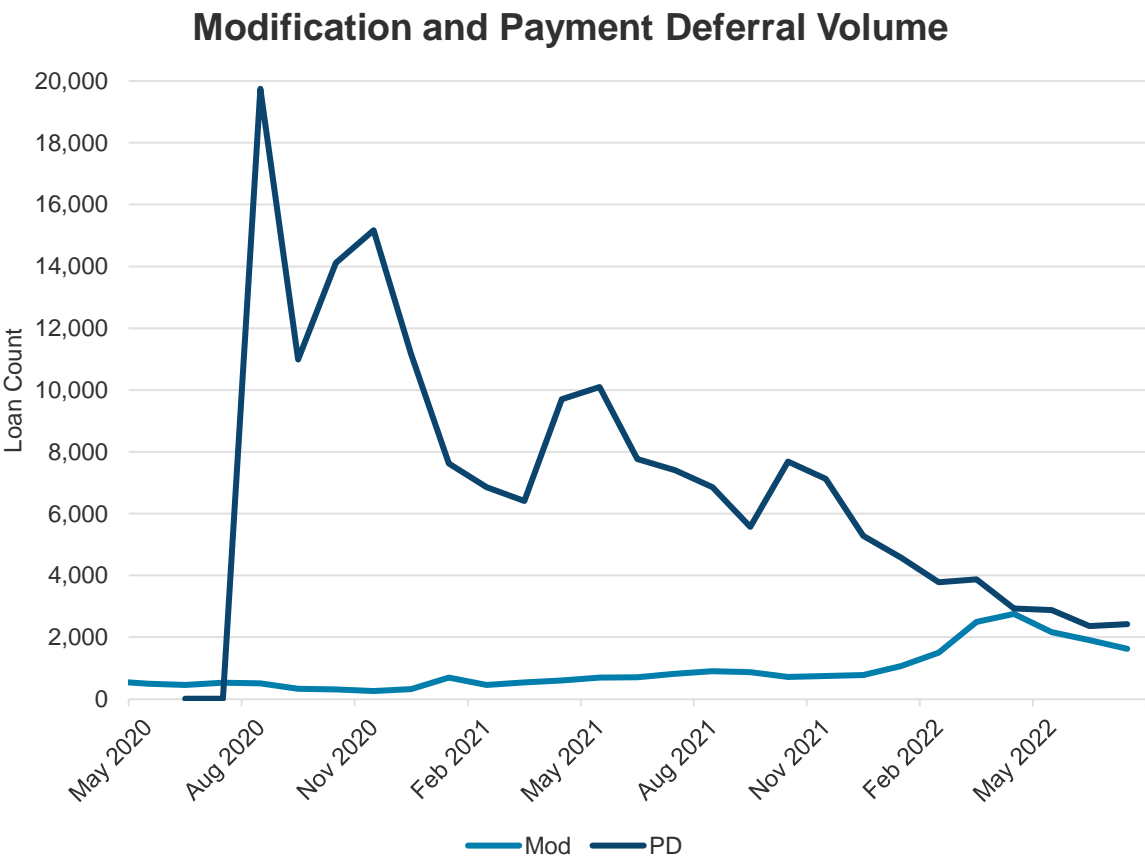
Source: Freddie Mac CRT Disclosure Data.

Models: Arrows in our Quiver
for Hitting Strategic Objectives

7/28/2022

Freddie Mac
Single-Family | Credit Risk Transfer

How Can Modern Modeling Methods Help Us Achieve Our Strategic Objectives?

Michael Bradley

Modeling, Econometrics, Data Science, and Analytics (MEDA)

Freddie Mac

Single-Family

The answer resides in understanding the answers to a couple of questions:

1. What is Machine Learning (ML)?

2. What are the benefits of ML and how are we managing its heightened risks?

3. How are we using ML to create value?

   o Loan Product Advisor (LPA) and Advanced Fair Lending Analytics

   o Collateral Condition Evaluator (CCE)

   o Automated Income-assessment Model (AIM)

What is Machine Learning (ML)?

Machine learning allows the computer to, in a sense, program itself. By making complex connections between data, the computer can create new useful information.

A particularly effective application of Machine Learning is Facebook's *learning algorithms*

"

ML Can Help Us Make Better Predictions!!

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What are the Benefits of ML?

Benefits of ML

- ✓ Machine Learning captures nonlinearities and interactions much better than traditional methods which maps to improved business outcomes

- ✓ ML has the potential to greatly improve outcomes (including expanding access to credit for protected-class borrowers)

- ✓ ML helps us identify new products / solutions for our clients

- ✓ Humans Predictably Make Mistakes "Thinking Fast and Slow" and smart machines help us work more effectively

Concerns / risks posed by ML?

ML Heightens Some Areas of Risk

- ✓ ML may perpetuate historical human bias

- ✓ ML algorithms may be difficult to interpret and explain, making it difficult for business folks to understand them and complicate adverse action notices

- ✓ ML platforms pose new types of risks

ML heightens some areas of model risk management

ML Regulatory Oversight

✓ **FHFA Establishes Office of Financial Technology**

- Focuses on sharing best practices and developing strategies for FHFA's regulated entities to advance housing finance fintech and innovation.

✓ **FHFA Advisory Bulletin on AI/ML Risk Management**

- Provides supervisory expectations for managing heightened and unique risks posed by use of AI/ML.

- Recognizes that AI/ML is an evolving field and encourages responsible innovation and use of AI/ML consistent with safe and sound operations.

✓ **Pending FHFA White Paper on AI/ML**

- The Federal Housing Finance Agency Office of Inspector General (OIG) is commencing a white paper on Enterprise Use of Artificial Intelligence and Machine Learning.

✓ **Recent CFPB Statements**
- Enforcements actions related to the use of AI are likely.

- Particular focus on "black boxes" that don't allow regulators and consumers to understand how decisions are made.

- Also concerns, sometimes with traditional data, but especially with alternative data—utility and rent payments—that may reflect historical biases.

ML Systems are not all "black boxes"

✓ Transparency can be achieved in one of two ways:

- **Directly interpretable ML model architectures**

  • Explainable boosting machines

  • Constrained tree-based models

  • Explainable neural networks

- **Post-hoc explanation of ML model decisions**

  • Shapley values / TreeSHAP

  • Partial dependency plots (PDPs)

  • Individual conditional expectation (ICE)

  • Local interpretable model-agnostic explanations (LIME)

The Need for Transparency can be Achieved!

Leveraging ML to Create Value:
New Modeling Development Efforts

Multi-year Effort to Modernize LPA

- Completed

  Brought LPA's loan scoring service in house.

  Acquired Experian's Attribute Tool Box (ATB) for processing credit files.

  Acquired Zest AI's machine learning platform (ZAML) to develop our models, provide explainability, and integrate more powerful Fair Lending tools..

- Application of Champion vs Challenger Framework

- Improved, data-driven model segments

- Innovative Fair Lending techniques

  o Apply Generative Adversarial Networks (GANs) to improve LPA's fairness while maintaining similar accuracy.
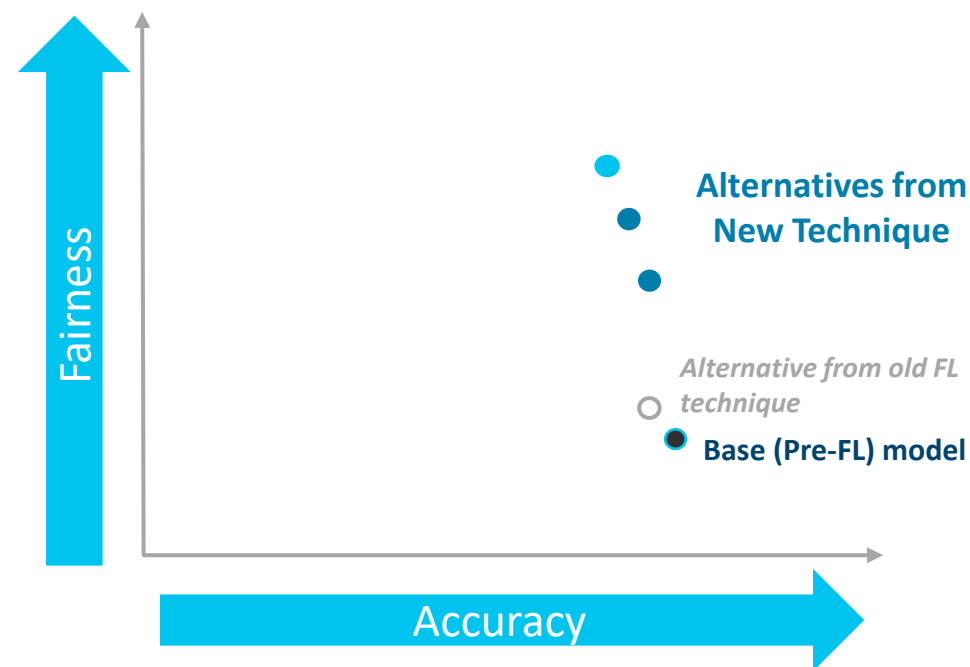
Bottom line: A flexible, fairer, more accurate, and more intuitive LPA that can safely expand homeownership opportunities for both minority and non-minority borrowers.

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LPA and Fair Lending Testing

Fair Lending testing of LPA uses innovative techniques to identify Less Discriminatory Alternatives

- A key component of the fair lending review of the model is a search for alternative model specifications that lower impact on protected classes without a material degradation in performance. If found, such alternatives are called **Less Discriminatory Alternatives or "LDA"s.**

- For LPA 7.9, we have employed an innovative adversarial debiasing technique using Generative Adversarial Networks (GANs) that **smartly** searches for alternative model specifications.

  - The new methodology performs a much wider search than the traditional drop-one methodology used for past LDA searches, which can allow it to find more optimal outcomes.

- By greatly expanding the search relative to previous methods, the GAN allows us to find much **larger improvements in fairness** than were possible before.

Alternatives from New Technique

Alternative from old FL technique

Base (Pre-FL) model

Fairness (vertical axis) / Accuracy (horizontal axis)

Results are hypothetical. Actual results are not shown.

Collateral Condition Evaluator

Developed model to better detect properties in poor condition and replace or complement ACE condition rules.

- Waive appraisals on fewer properties in poor condition.

- Waive appraisals on more properties in good condition.

❑ Applies Data Robot and **machine learning** in the cloud to research, develop, test, and deploy the model.

Text Pre-Processing: NLP Framework

- Computers are designed to work with structured data, follow well-defined commands, and use standardized language.

- Computers require Machine Learning to understand and work with Natural Language.
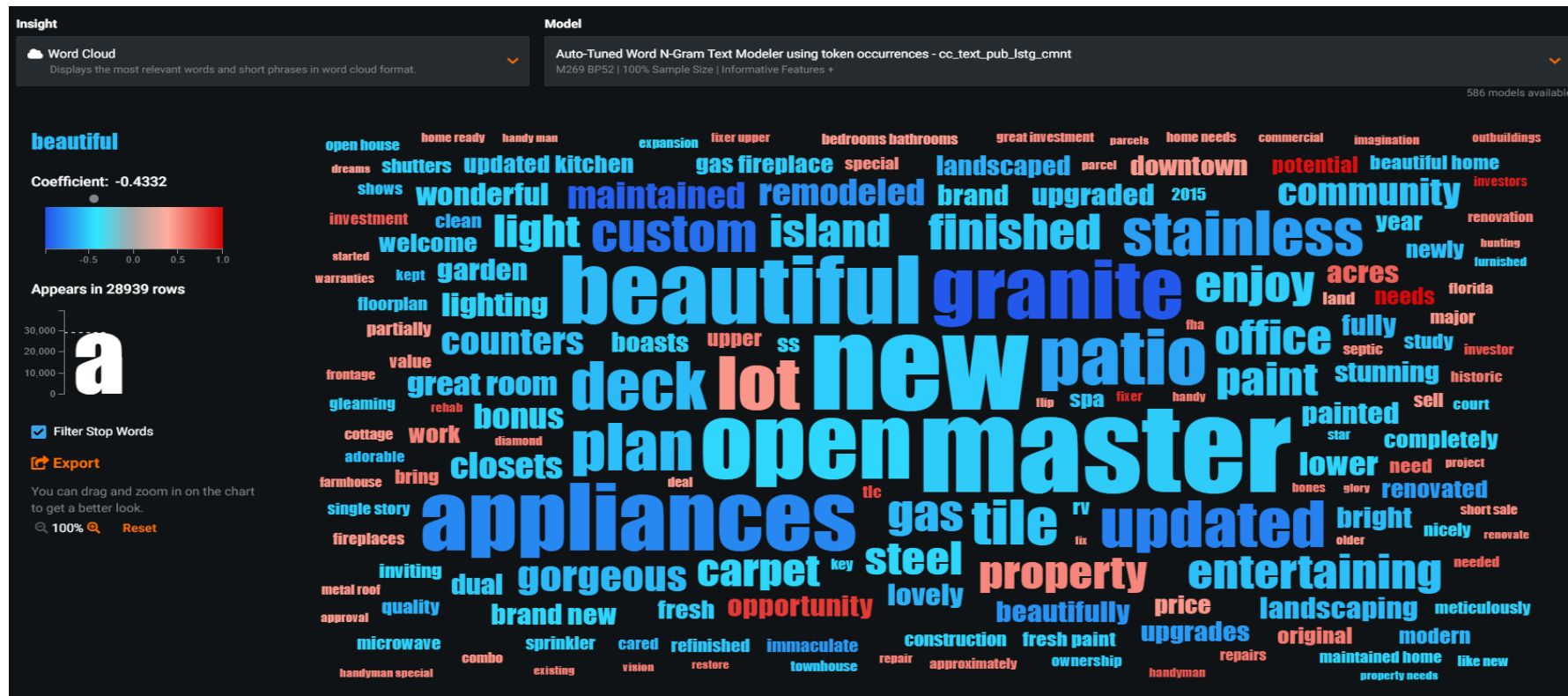
Which of these words (bags of words) are permitted from a FL perspective?.

What is AIM for Direct Deposit?

AIM for Direct Deposit is Loan Product Advisor's (LPA's) automated income assessment that leverages **account data** from trusted third-party service providers.

AIM assesses the following income:

- Base, Bonus, Overtime, Commission,
- Pension, Social Security, Military, Child Support/Alimony, and VA Disability

AIM leverages:

- Asset account details and transaction history
- Transaction description
- Patterns of pay deposits
- ML models

AIM uses the following trusted third-party Service Providers:

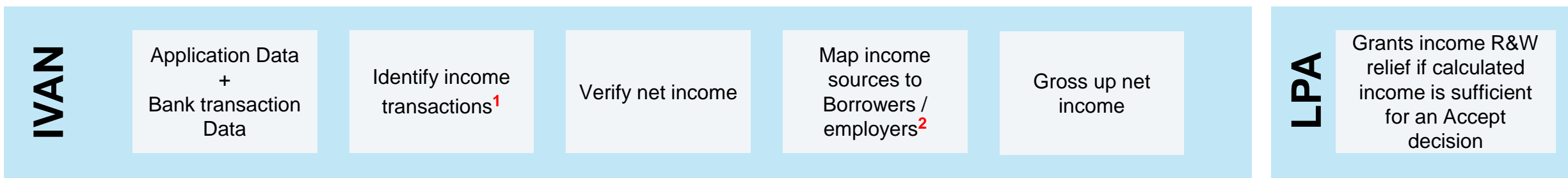- Finicity, FormFree, PointServ, and Blend
- Depository Institutions

40
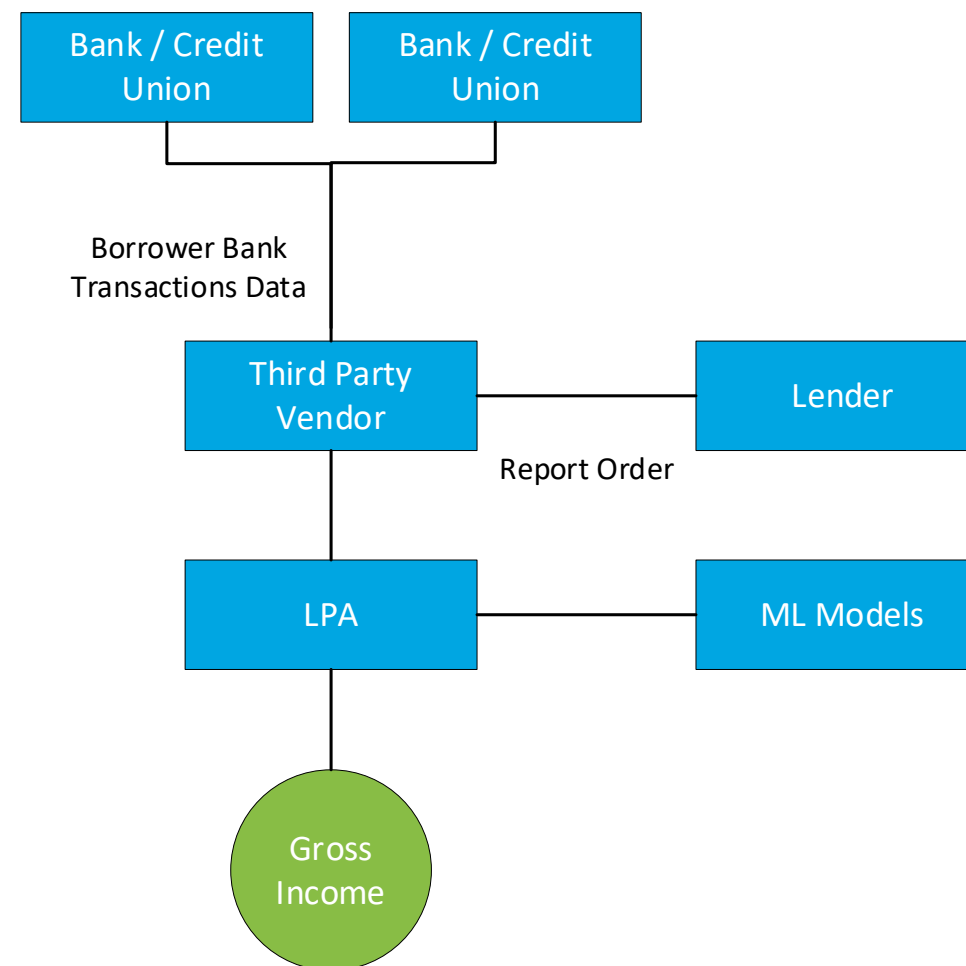
Using account data enables Freddie Mac to assess income for Borrowers

Automated Income Assessment Process

Assessment of account data is made possible by the IVAN application

- IVAN is a rules-based engine that uses **verified net income** in direct deposit transactions to derive grossed up income
- IVAN leverages two models (Labeler and Employer Name Match models)

IVAN	Application Data + Bank transaction Data	Identify income transactions[1]	Verify net income	Map income sources to Borrowers / employers[2]	Gross up net income	**LPA**	Grants income R&W relief if calculated income is sufficient for an Accept decision

1. IVAN calls the **Labeler model**. Input is transaction description, output is labeled transactions (e.g. Payroll, Pension, Social Security, Military Pay, Child Support, Alimony, VA Disability)

2. IVAN calls **Employer Name Match model**. Input is submitted employer name and transaction description employer name, output is confirmation of match or not

AIM for Direct Deposit uses a rules-based engine and ML models
to verify net income and gross up income for each Borrower and income type

Benefits of AIM for Direct Deposit

Comprehensive Risk Assessment	Remove Subjectivity	Leverage Big Data
▪ **Moves QC upfront on 100%** of assessed loans giving us a better understanding of the risk that we buy ▪ Data sourced directly from trusted service provider **prevents fraud** ▪ More data points than a summary view associated with a paystub/W-2 ▪ Direct deposit pay history allows for increased insight into stability of income, **increasing homeownership sustainability** ▪ Uniform calculation of income for all Borrowers	▪ Consistent application of rules ▪ **97%** of **income defects** would be **eliminated** when sufficient income is confirmed ▪ Fair and accurate assessment of Borrowers' capacity to repay	▪ Automated assessment enables Freddie Mac to evaluate more loans compared to a small sample of loans reviewed by QC ▪ Transaction data gathered on loans over time can be used to further enhance AIM offerings and set foundation for rent payment and cash flow analysis

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AIM for Direct Deposit improves the manufacturing quality of loans Freddie Mac purchases

Questions and Poll

Disclaimer

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